In the Claims

Claims 1 – 3 (Cancelled)

4. (Previously Presented) The method according to claim 16 in which the prediction models are formed by neural networks or other models for estimating functions that are each characteristic of a mode s and compete for description of individual elements of the time series according to predetermined training rules.

5. (Previously Presented) The method according to claim 16 in which the series of mixed system modes g_i is determined from the prediction models $f_{i,j}$ and interpolation parameters a, b according to $g_i = a(s)f_{i(s)}(x) + b(s)f_{j(s)}(x)$.

6. (Previously Presented) The method according to claim 5 in which the interpolation parameters are selected according to $0 < a(s) < 1$ and $b(s) = 1 - a(s)$.

7. (Previously Presented) The method according to claim 6 in which the values a(s) are restricted to a certain resolution figure R.

8. (Previously Presented) The method according to claim 16 in which the series of mixed prediction models g_i is detected by determining a prediction for each time increment with each of the possible prediction models, resulting in a time-dependent prediction matrix from which a mean prediction error for randomly selected segmentations can be derived, whereby a sought series of mixed prediction models g_i is the segmentation with the smallest prediction error or the maximum probability.

9. (Previously Presented) The method according to claim 8 in which the search for the segmentation with the smallest prediction error is made by a dynamic programming technique that is equivalent to the Viterbi algorithm for hidden Markov models, whereby an optimum sequence of

prediction models is determined using a minimized cost function $C^\star$ of the prediction and the segmentation is derived inductively from the sequence of prediction models.

10. (Previously Presented) The method according to claim 16 in which drift segmentation is followed by an additional step to reduce the number of prediction models used for modeling where the number of prediction models is reduced sequentially, associated with a determination of the mean prediction error, until a further reduction of the number of prediction models means an increase in the prediction error.

11. (Previously Presented) The method according to claim 16 in which the time series of at least one of the system variables x(t) comprises a time series of physiological parameters described by the Mackey-Glass delay differential equation $dx(t) / dt = -0.1x(t) + 0.2x(t - t_d) / 1 + x(t - t_d)^{10}$.

12. (Previously Presented) The method according to claim 16 in which the time series of at least one of the system variables x(t) comprises a time series of physiological parameters that are characteristic of a development of sleep and wake modes.

13. (Previously Presented) The method according to claim 12 in which the physiological parameters comprise EEG signals.

14. (Previously Presented) The method according to claim 16 in which the time series of at least one of the system variables x(t) comprises a time series of speech signals.

15. (Cancelled)

16. (Currently Amended) A method performed on a computer for detecting modes of a dynamic system in a physical, chemical or biological process with a multiplicity of modes s_i that each have a set $\alpha(t)$ of characteristic system parameters comprising the steps of:

performing a switch segmentation of a time series of at least one system variable x(t), in which the switch segmentation is a simulation of a training time series of the system or of the time

series to be investigated with several, competing prediction models,

detecting predetermined prediction models f_i for system modes s_i for each system variable x(t) in each time segment of a predetermined minimum length,

deriving a system model by performing a drift segmentation subsequent to said switch segmentation in which, in each time segment in which there is a transition of the system from a first system mode s_i to a second system mode s_j, a series of mixed prediction models g_i is detected and produced by linear, paired superimposition of prediction models $f_{i,j}$ of the two system modes $s_{i,j}$, ~~and~~

~~predicting a state of said dynamic system in the physical, chemical or biological process, directly following to a current state, based on the detected current modes.~~

detecting a current system mode corresponding to a current state of the dynamic system; and

applying the derived system model to the detected current system mode to determine a state of the dynamic system in the physical, chemical or biological process, that directly follows the current state.

17. (Currently Amended) A method performed on a computer for detecting modes of a dynamic system in a physical, chemical or biological process with a multiplicity of modes s_i that each have a set α(t) of characteristic system parameters comprising the steps of:

performing a switch segmentation of a time series of at least one system variable x(t), in which the switch segmentation is a simulation of a training time series of the system or of the time series to be investigated with several, competing prediction models,

detecting predetermined prediction models f_i for system modes s_i for each system variable x(t) in each time segment of a predetermined minimum length,

deriving a system model by performing a drift segmentation subsequent to said switch segmentation in which, in each time segment in which there is a transition of the system from a first

system mode s_i to a second system mode s_j, a series of mixed prediction models g_i is detected and produced by linear, paired superimposition of prediction models $f_{i,j}$ of the two systems modes $s_{i,j}$, and

controlling said dynamic system in the physical, chemical or biological process, ~~including~~ via determining a deviation of a current state of said dynamic system from a setpoint state using the derived system model and deriving a control strategy on the basis of said deviation.

18. (Previously Presented) The method according to claim 6 in which the values a(s) are equidistant.

19. (Previously Presented) The method according to claim 17 in which the prediction models are formed by neural networks or other models for estimating functions that are each characteristic of a mode s and compete for description of individual elements of the time series according to predetermined training rules.

20. (Previously Presented) The method according to claim 17 in which the series of mixed system modes g_i is determined from the prediction models $f_{i,j}$ and interpolation parameters a, b according to $g_i = a(s)f_{i(s)}(x) + b(s)f_{j(s)}(x)$.

21. (Previously Presented) The method according to claim 20 in which the interpolation parameters are selected according to $0 < a(s) < 1$ and $b(s) = 1 - a(s)$.

22. (Previously Presented) The method according to claim 21 in which the values a(s) are restricted to a certain resolution figure R.

23. (Previously Presented) The method according to claim 17 in which the series of mixed prediction models g_i is detected by determining a prediction for each time increment with each of the possible prediction models, resulting in a time-dependent prediction matrix from which a mean prediction error for randomly selected segmentations can be derived, whereby a sought series of mixed prediction models g_i is the segmentation with the smallest prediction error or the maximum

probability.

24. (Previously Presented) The method according to claim 23 in which the search for the segmentation with the smallest prediction error is made by a dynamic programming technique that is equivalent to the Viterbi algorithm for hidden Markov models, whereby an optimum sequence of prediction models is determined using a minimized cost function C^* of the prediction and the segmentation is derived inductively from the sequence of prediction models.

25. (Previously Presented) The method according to claim 17 in which drift segmentation is followed by an additional step to reduce the number of prediction models used for modeling where the number of prediction models is reduced sequentially, associated with a determination of the mean prediction error, until a further reduction of the number of prediction models means an increase in the prediction error.

26. (Previously Presented) The method according to claim 17 in which the time series of at least one of the system variables x(t) comprises a time series of physiological parameters described by the Mackey-Glass delay differential equation $dx(t) / dt = -0.1x(t) + 0.2x(t - t_d) / 1 + x(t - t_d)^{10}$.

27. (Previously Presented) The method according to claim 17 in which the time series of at least one of the system variables x(t) comprises a time series of physiological parameters that are characteristic of a development of sleep and wake modes.

28. (Previously Presented) The method according to claim 27 in which the physiological parameters comprise EEG signals.

29. (Previously Presented) The method according to claim 17 in which the time series of at least one of the system variables x(t) comprises a time series of speech signals.

30. (Previously Presented) The method according to claim 21 in which the values a(s) are equidistant.